# Parking Camera Calibration for Assisting Automated Road Defect Detection 

Stefania C. Radopoulou ${ }^{1}$, and Ioannis Brilakis ${ }^{2}$<br>1) Ph.D. Candidate, Department of Engineering, University of Cambridge, Cambridge, UK. Email: scr58@cam.ac.uk<br>2) Laing O'Rourke Lecturer, Department of Engineering, University of Cambridge, Cambridge, UK. Email:<br>ib340@cam.ac.uk


#### Abstract

: Accurate and timely information is essential for efficient road maintenance planning. Current practice mainly depends on manual visual surveys that are laborious, time consuming, subjective and not frequent enough. We overcame this limitation in our previous work, by proposing a method that automatically detects road defects in video frames collected by a parking camera. The use of such a camera leads to capturing the surroundings of the road, such as sidewalks and sky due to its wide field of view. This unnecessarily reduces the method's performance. This paper presents a process that identifies the correct Region of Interest (myROI). myROI corresponds to the region of the camera's field of view that corresponds to the road lane, while considering defect inspection guidelines. We use the theory of inverse perspective mapping (IPM) to map the road frame coordinates to world coordinates. The camera specifications, and position, lane width and road defect detection guidelines constitute the parking camera calibration parameters for the calculation of myROI's span and boundaries. We performed computational experiments in MATLAB to calculate myROI, and validated the results with field experiments, where we used a metric tape to measure the road defects. Preliminary results show that the proposed process is capable of calculating myROI.


Keywords: Region of interest, inverse perspective mapping.

## 1. INTRODUCTION

According to the International Infrastructure Maintenance Manual (NAMS Group 2006), an asset management system must have knowledge of the following: 1) existing assets, 2) the assets' condition, and 3) the level of service the assets can provide . This shows the importance of road condition assessment, which is a pre-requisite for designing, planning and determining maintenance programs. In the UK, a report written by the Department for Transport and the Highways Agency claims there is insufficient road condition data, and gaps exist in the collected information (National Audit Office 2014).

Current road condition monitoring process consists of the following steps: 1) road data collection, 2) defect identification, 3) defect assessment, and 4) road condition index (RCI) calculation. Data collection is performed either manually or automatically. Inspectors walk along the road or drive around the network to look for irregularities during manual data collection. Vehicles equipped with several sensors, such as laser scanners and image cameras are utilized for automated data collection.

In the case of manual inspections, all collected data is inserted into the road authority's database once the inspection is done. Such data consist of images from the defects found accompanied by qualitative descriptions. If a defect is repaired on the spot, images from before and after the inspector's intervention are required. A description of the action that he/she took is also expected. If it is not possible to repair the defect on the spot, the inspector characterizes the urgency of the required action. Thus, defect identification and assessment is performed along with the data collection when it is performed manually. However, it is obvious that it is a laborious and time-consuming task.

The same holds for the automated data collection, the second and third steps of which are manual. Inspectors view all collected data on multiple screens and search for defects. Although defect assessment is performed using well-written guidelines, it is inevitable that the inspector's subjectivity will influence the process according to his/her level of experience (Bianchini et al. 2010). The subjectivity of these results is another limitation of the current practice. Finally, the Road Condition Index (RCI) is calculated for road segments according to the number, type, and severity of defects encountered. RCI is the metric most often used for prioritizing maintenance actions.

The main problem that this paper focuses on is the extraction of metrics from the collected data. As aforementioned, inspectors are using guidelines for identifying defects and categorizing them in levels of severity. Each defect is described with its different attributes using geometrical characteristics, such as length, width and depth. In the case of visual surveys, inspectors are using tapes to measure such attributes. In the case of automatically collected data, the software that accompanies the sensors calculates the metrics automatically, or inspectors are deriving them manually. Except for the automatically calculated metrics, the other ways of
performing it are laborious and time consuming.
The goal of this research is to develop a low-cost automated road condition monitoring method to address the limitations of current practice. The idea is to use crowdsourcing to transition the task of monitoring from road inspectors to every day road users by transforming them into ubiquitous reporters. In our previous work (Radopoulou and Brilakis 2015), we proposed the use of parking cameras, a sensor that already exists in multiple passenger vehicles and is mandated to be attached to all such vehicles in the USA by 2018 (NHTSA 2014). This paper presents a method for isolating the road lane in the parking camera's field of view while taking into consideration the metrics of defects that inspectors are using when they are looking for defects and during the assessment.

## 2. STATE OF RESEARCH

Several studies have focused on the problem of road or lane detection due to the increasing demand of advanced driver assistance systems. Systems that alert the driver to dangerous situations or assist with driving are continuously developed and added in passenger vehicles. Various hardware setups have been proposed for road/lane detection (Hillel et al. 2014).

Light Detection And Ranging (LIDAR) systems were utilized to identify objects obstructing the visibility of lane markings and road boundaries (Hernández and Marcotegui 2009; Huang et al. 2009), estimate the roughness of the road (Huang et al. 2009; Kammel and Pitzer 2008) and detect road edges, curbs and berms etc. (Hernández and Marcotegui 2009; Nefian and Bradski 2006; Urmson et al. 2009). The high cost of LIDAR sensors limits the practical use of these methods. Although several companies provide LIDAR sensors commercially, the cost remains high.
Stereo imaging, a concept that uses two cameras in order to reconstruct the captured three-dimensional (3D) scene, was proposed for solving the problem of road/lane detection. It was used for road pitch angle, 3D geometry and slope estimation (Danescu and Nedevschi 2009), and curb detection (Pradeep et al. 2008). Although stereo imaging is a much cheaper solution than LIDAR, it cannot reach the same level of accuracy and reliability. Additionally, it poses a greater challenge for data processing (Hillel et al. 2014) because its range accuracy depends on the distance between the cameras. The reliability of the results increases as the distance of the cameras increases, and the same holds true for the computational cost.
Geographic Information Systems (GIS), Geographic Positional Systems (GPS) and Inertial Measurement Units (IMU) are also gaining popularity for assisting driver navigation. GPS devices have an accuracy of 5-10m (Wing et al. 2005) which can be reduced to 1 m with the addition of an IMU (Urmson et al. 2009). The limitation of such systems lies in their reliability due to their dependency on multiple satellite connections. Although in many areas the information provided is accurate, GPS can lose signal in others. IMUs can compensate for such a loss, but to a limited extent. Internal vehicle dynamic sensors that measure speed, yaw rate, and acceleration (e.g. wheel speed and stirring angle sensors) were also used in conjunction with other sensors (Labayrade et al. 2006; McCall and Trivedi 2006). However, their accuracy is limited (Huang et al. 2009).
Many methods in the literature propose the use of a single camera for road/lane detection. In most cases, the camera is positioned in the middle of the vehicle looking forward. Image-based methods usually start with an image pre-processing step and continue with feature extraction for detecting the object in question. Pre-processing techniques aim to handle illuminations (Huang et al. 2009) and remove shadows (Cheng et al. 2006; Katramados et al. 2009). Feature extraction usually aims to detect lane markings, which have distinctive shape and colour in comparison to the rest of the road. Simple gradients (Nieto et al. 2008; Samadzadegan et al. 2006) and steerable filters (McCall and Trivedi 2006) were used for this purpose.

Another approach in pre-processing image-based methods is to calculate the Region of Interest in the image. Several definitions were used. It can be either the lower half of the image (Zhang et al. 2009) or the mapping of 3D world coordinates to the 2D image (Bertozzi and Broggi 1998; Huang et al. 2009; Tapia-Espinoza and Torres-Torriti 2013; Zhang et al. 2009). In the case that the lower half of the image is defined as the region of interest, the problem of identifying where the road lane is within that part of the frame still remains in some cases. The reason it doesn't hold for all cases is because it is dependent on the camera's specifications and positions. If the camera has a small horizontal field of view and is positioned closer to the ground, then the lower half of the image might only contain the road lane, but if it is wide and is positioned further away from the road level, then it will include the surrounding of the lane as well. Hence, defining the region of interest as the lower half of the image is quite abstract.

The theory of Inverse Perspective Mapping (IPM) makes use of the camera's position and orientation to perform the mapping. Here follows an explanation of IPM, which is calculated using the pinhole model and the following assumptions:

1) The world coordinate system is fixed to the vehicle, $\left\{x^{w}, y^{w}, z^{w}\right\}$
2) The camera is positioned at the back of the vehicle, at the middle of its width, at a height $h$ with respect to the ground and is tilted by an angle $\theta_{0}$ towards the plane of the road.

Figure 1 depicts the IPM model. Equations 1 and 2 describe the relationship between a point $p$ in the 2 D image plane and its 3D position P in the world. The image plane has size $m x n$ pixels. The point p in the image plane is represented with the image coordinate pair $(u, v)$, where $u$ is the horizontal axis of the camera and $v$ us the vertical axis. Point p can also be represented with the pair $(r, c)$ if we consider the standard image row-column representation of the image plane.


Figure 1. Inverse Perspective Mapping model of a point P in the world to a point p in the image.

$$
\begin{align*}
x(r) & =h\left(\frac{1+\left[1-2\left(\frac{r-1}{m-1}\right)\right] \tan \left(a_{v}\right) \tan \left(\theta_{0}\right)}{\tan \left(\theta_{0}\right)-\left[1-2\left(\frac{r-1}{m-1}\right)\right] \tan \left(a_{v}\right)}\right)  \tag{1}\\
y(r, c) & =h\left(\frac{\left[1-2\left(\frac{c-1}{n-1}\right)\right] \tan \left(a_{u}\right)}{\sin \left(\theta_{0}\right)-\left[1-2\left(\frac{r-1}{m-1}\right)\right] \tan \left(a_{v}\right) \cos \left(\theta_{0}\right)}\right) \tag{2}
\end{align*}
$$

where $\quad r, c$ : image coordinates
$m, n$ : image coordinates
$h$ : height of the camera in respect to the ground
$\theta_{0}$ : angle formed by the camera when tilted towards the road plane in respect to an axis parallel to $x^{w}$ that goes through the focal point

$$
a_{u}: \text { camera's vertical angle of view }
$$

$a_{v}$ : camera's horizontal angle of view
Existing methods have focused on automating the detection of the road lane. However, some are doing it quite abstractly, or are just detecting the road lane, which in our case isn't useful. We are interested into incorporating the inspection guidelines and the defects' metrics used for their assessment. Hence, the research question we set is: what is the region of interest in a road video frame that is of use to an inspector? And our objective in this paper is to propose such a method, which will isolate that part of the video frame that includes the road lane
where defects can actually be detected.

## 3. PROPOSED SOLUTION

We assume that the parking camera is positioned on the rear of the vehicle looking backwards, at approximately its middle and usually either close to the sign plate or the trunk handle. This is based on the position of typical parking cameras which are placed either close to the sign plate of the vehicle or close to the trunk handle, depending on the design of the car. The cameras used are often rotated downwards and have wide angles of view, usually exceeding 90 degrees both horizontally and vertically.

Due to this setup, captured video frames depict not only the road lane, but its surroundings as well. These include other vehicles, adjacent lanes, nature, sky, etc. Such features do not describe the condition of the road, and are considered extraneous information. Therefore, a method is needed to isolate the road lane from the rest of the video frame to allow further processing. However, even if the road lane is isolated from the rest of the image, not all of it will be useful to an inspector. This is because based on the image analysis of the camera used, the detail that is provided isn't across all pixel rows. Hence, this needs to be taken into consideration. We call the portion of each video frame that contains useful information myROI (my Region of Interest), and we calculate it using the following:

1) Equations of IPM
2) Camera's position (relative to the ground and centre of vehicle) and specifications (image analysis, lens' angles of view-horizontally and vertically)
3) Road lane width
4) Inspection defect detection guidelines

Initially, using the camera's position (height with respect to the ground) and specifications, we match the pixels of a video frame with the real world space by using the equations of IPM. At this point, the image analysis of the camera used is critical, because it defines the amount of detail that the image can capture. Knowing the world coordinates that each pixel represents, then follows the calculation of the distance that each consecutive row in the image is representing. This information allows to define the upper bound of myROI, along with the smaller width of transverse crack that needs to be detected. Finally, the side boundaries of myROI are calculated based on the width of the road lane that is being travelled.


Figure 2. Process of calculating myROI

## 3. IMPLEMENTATION \& RESULTS

The code was implemented in MATLAB. The initial calculations were performed using the characteristics of the camera that was selected according to parking camera standards, which is 0.4 MP resolution $-808 \times 508$ pixels (PG BFLY 05S2M). A lens that provides wide angles of view (Sunex DSL212) was attached to the camera to acquire the desired perspective $-133^{\circ}$ horizontal angle of view and $102^{\circ}$ vertical angle of view. Figure 3 shows the hardware used. The same standards were used for positioning the camera on the rear of the vehicle, 0.65 m above ground, and approximately 5 cm left from the middle of the vehicle (see figure 3). For deciding on the defects' sizes, table 1 was created based on several inspection defect detection guidelines (FHWA 2003; MnDOT 2003; MTC 1991; SDDOT 2009; UKPMS 2005). Table 1 summarizes the overall minimum and maximum of defects' attributes. Figure 4 and table 2 depict the results achieved using the aforementioned setup. Table 2 includes details for myROI considering higher resolution cameras as well.


Figure 3. Left - Hardware used for the calculation of myROI; Right - The position of the camera at the rear of a vehicle

Table 1. Minimums and maxima of defects' attributed that inspectors' are looking for

| Defect | Attribute | Severity | Overall minimum | Overall maximum |
| :---: | :---: | :---: | :---: | :---: |
| Longitudinal crack | Width | Low <br> Medium <br> High | 2 mm | $\begin{gathered} 6 \mathrm{~mm} \\ 6-19 \mathrm{~mm} \\ 20 \mathrm{~mm} \end{gathered}$ |
|  | Length | Low <br> Medium <br> High | $\begin{aligned} & <0.9 \mathrm{~m} \\ & >0.9 \mathrm{~m} \end{aligned}$ | 1 m |
| Transverse cracks | Width | Low <br> Medium <br> High | 3 mm <br> up to 6.35 mm $>6.35 \mathrm{~mm}$ | $\begin{gathered} \hline 6.35 \mathrm{~mm} \\ \text { up to } 20 \mathrm{~mm} \\ >20 \mathrm{~mm} \end{gathered}$ |
|  | Length | Low <br> Medium <br> High | >0.6m | <1.82m |
| Alligator Cracking |  | $\begin{gathered} \text { Low } \\ \text { Medium } \\ \text { High } \end{gathered}$ | $<6 \mathrm{~mm}$ width \& no further than 150 mm apart <br> $>6 \mathrm{~mm} \&<=19 \mathrm{~mm} \& \&$ no further than 150 mm apart $>19 \mathrm{~mm}$ |  |
| Potholes | Depth | Low <br> Medium <br> High | $\begin{gathered} <25 \mathrm{~mm} \\ 25-50 \mathrm{~mm} \\ >50 \mathrm{~mm} \end{gathered}$ |  |
|  | Area | Low Medium High | $15 \times 15 \mathrm{~cm}$ | $>175 \mathrm{~cm} 2$ |
|  | Width | Low <br> Medium <br> High | palm size dinner plate larger | >150mm |
| Local Settlement (depression) | Level difference | Low Medium High | $\begin{gathered} 3 \text { to } 6 \mathrm{~mm} \\ 7 \text { to } 13 \mathrm{~mm} \\ >13 \mathrm{~mm} \end{gathered}$ | $\begin{gathered} 3.175-50 \mathrm{~mm} \\ \text { up to } 101 \mathrm{~mm} \\ >101 \mathrm{~mm} \end{gathered}$ |
| Patching | number | Low Medium High | $\begin{aligned} & \hline \hline 1-3 \text { per } 30.5 \mathrm{~m} \\ & 4-6 \text { per } 30.5 \mathrm{~m} \\ & >6 \text { per } 30.5 \mathrm{~m} \end{aligned}$ |  |

## 4. DISCUSSION \& CONCLUSIONS

Current practice for road condition monitoring is predominantly manual. It suffers from the limitations of being time consuming and laborious. In addition, it is inevitable that the subjectivity of the inspector influences the assessment results. Hence, state of research has turned its focus on automating the process and in particular, the detection of road defects.
The project we have been working on lately focuses on proposing a method for automatically detecting road defects using parking cameras. Due to our intention of utilizing such a sensor, which is accompanied with wide angle of views lenses and it captures extraneous surrounding details in addition to the road lane, in this paper we propose a method for isolating that part of the video frame that is useful for an inspector. We used the theory of Inverse Projection Mapping along with camera calibration information to accomplish this task. This included the camera's position in respect to the road plane and the vehicle, its analysis, and its angles of views. The defect attributes (sizes) that inspectors are looking for during a road assessment were also used.

The calculation of myROI was performed in MATLAB. The specifications of a typical parking camera, including its recommended position, were used. It was concluded that the size of the defect defines the upper bound of myROI; i.e. the finer the defect, the smaller the area of interest. This justifies the lower upper boundary of the red polygon in figure 4, within which the minimum width of a transverse crack that can be detected is 3.175 mm ; this corresponds to the smaller width that is encountered in the inspector's guidelines. In the real world, this translates to 30.8 cm away from the back of the vehicle (see figure 4). If a wider transverse crack is to be searched for, then the area of myROI increases and its upper bound is extended. So a transverse crack of 6.35 mm width can be found within the green polygon of figure 4 . The green bounded myROI corresponds to 62.82 cm away from the vehicle.

The camera's analysis is another factor that affects the boundaries of myROI. This is evident from the calculations of myROI using higher camera resolution. As video analysis increases, so does the area of myROI. However, that results in an increase of the cost for the hardware. The camera's orientation is also affecting myROI, along with the angle of views of the camera's lens. It is critical that the camera is positioned at such a height and tilted downwards in that angle, so that it doesn't include the back of the car. The higher the camera is positioned, the bigger the rotation downwards should be, so that myROI covers the area exactly opposite to the car. That is where the analysis of the image is finer as well.
An important aspect for the calculation of myROI using the methodology presented in this paper is to know the width of the road lane that the car is driving on. Hence, in our future work, we are interested in incorporating an automated method for calculating the width of the road lane. Moreover, in figure 5 it is obvious that there is some distortion, which is due to the wide-angle views of the parking camera. However, this does not affect the defect detection results so it is not corrected in the input. For future work, correction of this type of distortion will be part of the data pre-processing. In general, the advantage of the method proposed in this paper is that it is incorporating the needs of road inspectors for whom it is critical to detect defects of specific sizes. It is very helpful and saves from their time to provide them with the area that they should be looking into. The results show that the method is promising


Figure 4. Left- Depiction of myROI on top of a video frame captured by a parking camera (trans holds for transverse); a transverse crack with 3.175 mm width can be found within the red shape, a transverse crack with 6 mm width can be found within the green shape and one with 1 cm can be found within the magenta shape, Right- Depiction of extension of myROI at the back of a vehicle


Figure 5. Upper left- Longitudinal crack (enclosed in yellow ellipse) of approximately 3 mm shown in the middle of myROI, Upper right) Patch (enclosed in yellow box) with dimensions: upper side -120 cm , lower side- 135 cm , right side 135 cm \& left side 142 cm , shown in myROI, Lower) Patch (enclosed in yellow ellipse) of 95 cm width on the left and a pothole (enclosed in yellow ellipse) with 10 cm diameter on the right shown in myROI

Table 2. myROI results for different camera resolutions

| Camera resolution | myROI <br> upper <br> bound <br> (row) | myROI <br> upper <br> bound <br> (pixels) | min <br> Long <br> crack <br> width <br> (mm) | min <br> Long crack width (pixels) | max <br> Long <br> crack <br> length | max <br> Long crack length (pixels) | min <br> Trans crack width | min Trans crack width (pixels) | max <br> Trans <br> crack <br> length <br> (m) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{gathered} 808 \times 508 \\ (0.4 \mathrm{MP}) \end{gathered}$ | $\begin{aligned} & \hline 355 \\ & 282 \\ & 277 \\ & 239 \\ & 195 \end{aligned}$ | $\begin{aligned} & \hline 153 \\ & 226 \\ & 231 \\ & 269 \\ & 313 \end{aligned}$ | 2.5 | 2 | 30.8 cm <br> 62.82 cm <br> 65.91 cm <br> 96.1 cm <br> 1.57 cm | 808 | $\begin{gathered} \hline 3.175 \mathrm{~mm} \\ 6 \mathrm{~mm} \\ 6.35 \mathrm{~mm} \\ 1 \mathrm{~cm} \\ 2 \mathrm{~cm} \\ \hline \end{gathered}$ | 2 | 2.19 |
| $\begin{gathered} 1024 \times 768 \\ (0.7 \mathrm{MP}) \end{gathered}$ | $\begin{aligned} & \hline 461 \\ & 365 \\ & 318 \\ & 264 \end{aligned}$ | $\begin{aligned} & \hline 307 \\ & 373 \\ & 450 \\ & 504 \end{aligned}$ | 1.9 | 2 | $\begin{gathered} \hline 50 \mathrm{~cm} \\ 93.55 \mathrm{~cm} \\ 1.31 \mathrm{~m} \\ 2.07 \mathrm{~m} \end{gathered}$ | 1024 | $\begin{gathered} \hline 3.175 \mathrm{~mm} \\ 6.35 \mathrm{~mm} \\ 1 \mathrm{~cm} \\ 2 \mathrm{~cm} \end{gathered}$ | 2 | 2.19 |
| $\begin{gathered} 1280 \times 960 \\ (1 \mathrm{MP}) \end{gathered}$ | $\begin{aligned} & 533 \\ & 426 \\ & 373 \\ & 312 \end{aligned}$ | $\begin{aligned} & 427 \\ & 534 \\ & 587 \\ & 648 \end{aligned}$ | 1.5 | 2 | $\begin{gathered} 62.6 \mathrm{~cm} \\ 1.1 \mathrm{~m} \\ 1.53 \mathrm{~m} \\ 2.39 \mathrm{~m} \end{gathered}$ | 1280 | $\begin{gathered} \hline 3.175 \mathrm{~mm} \\ 6.35 \mathrm{~mm} \\ 1 \mathrm{~cm} \\ 2 \mathrm{~cm} \end{gathered}$ | 2 | 2.21 |

## ACKNOWLEDGEMENTS

This material is based in part upon work supported by the National Science Foundation under Grant Number 1031329. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

## REFERENCES

ASCE. (2013). "2013 report vehicled for America's infrastructure." [http://www.infrastructurereportvehicled.org/](http://www.infrastructurereportvehicled.org/) (Jul. 20, 2013).

Bertozzi, M., and Broggi, A. (1998). "GOLD: A parallel real-time stereo vision system for generic obstacle and lane detection." Image Processing, IEEE Transactions on, 7(1), 62-81.
Bianchini, A., Bandini, P., and Smith, D. W. (2010). "Interrater reliability of manual pavement distress evaluations." Journal of Transportation Engineering, 136(2), 165-172.
CBI, and KPMG. (2011). "Making the right connections: CBI/KPMG infrastructure survey 2011."
CBI, and URS. (2014). Taking the long view: a new approach to infrastructure. Infrastructure survey, UK.
Cheng, H.-Y., Jeng, B.-S., Tseng, P.-T., and Fan, K.-C. (2006). "Lane detection with moving vehicles in the traffic scenes." Intelligent Transportation Systems, IEEE Transactions on, 7(4), 571-582.
Danescu, R., and Nedevschi, S. (2009). "Probabilistic lane tracking in difficult road scenarios using stereovision." Intelligent Transportation Systems, IEEE Transactions on, 10(2), 272-282.
FHWA. (2003). Distress Identification Manual for the Long-Term Pavement Performance Program. Federal Highway Administration.
Hernández, J., and Marcotegui, B. (2009). "Filtering of artifacts and pavement segmentation from mobile lidar data." ISPRS Workshop Laserscanning 2009.
Hillel, A. B., Lerner, R., Levi, D., and Raz, G. (2014). "Recent progress in road and lane detection: a survey." Machine Vision and Applications, 25(3), 727-745.
Huang, A. S., Moore, D., Antone, M., Olson, E., and Teller, S. (2009). "Finding multiple lanes in urban road networks with vision and lidar." Autonomous Robots, 26(2-3), 103-122.
ICE. (2014). The state of the nation - Infrastructure 2014. Institution of Civil Engineers.
Kammel, S., and Pitzer, B. (2008). "Lidar-based lane marker detection and mapping." Intelligent Vehicles Symposium, 2008 IEEE, IEEE, 1137-1142.
Katramados, I., Crumpler, S., and Breckon, T. P. (2009). "Real-time traversable surface detection by colour space fusion and temporal analysis." Computer Vision Systems, Springer, 265-274.
Labayrade, R., Douret, J., Laneurit, J., and Chapuis, R. (2006). "A reliable and robust lane detection system based on the parallel use of three algorithms for driving safety assistance." IEICE transactions on information and systems, 89(7), 2092-2100.
McCall, J. C., and Trivedi, M. M. (2006). "Video-based lane estimation and tracking for driver assistance: survey, system, and evaluation." Intelligent Transportation Systems, IEEE Transactions on, 7(1), 20-37.
MnDOT. (2003). "Mn/DOT Distress Identification Manual." Minnesota Department of Transportation.
MTC. (1991). Pavement Condition Index Distress Identification Manual for Jointed Portland Cement Concrete Pavements. TDD/TTY, Metropolitan Transportation Commision, Oakland, CA.
NAMS Group. (2006). International infrastructure management manual. National Asset Management Steering Group.
National Audit Office. (2014). Maintaining stategic infrastructure: roads. Summary, National Audit Office, UK.
Nefian, A. V., and Bradski, G. R. (2006). "Detection of drivable corridors for off-road autonomous navigation." Image Processing, 2006 IEEE International Conference on, IEEE, 3025-3028.
NHTSA, 2014. (2014). "Federal Motor Vehicle Safety Standards; Rear Visibility." FEDERAL REGISTER-The Daily Journal of the United States Government, <https://www.federalregister.gov/articles/2014/04/07/2014-07469/federal-motor-vehicle-safety-standards-rear-visib ility> (May 6, 2014).
Nieto, M., Salgado, L., Jaureguizar, F., and Arróspide, J. (2008). "Robust multiple lane road modeling based on perspective analysis." Image Processing, 2008. ICIP 2008. 15th IEEE International Conference on, IEEE, 2396-2399.
Pradeep, V., Medioni, G., and Weiland, J. (2008). "Piecewise planar modeling for step detection using stereo vision." Workshop on computer vision applications for the visually impaired.
Radopoulou, S. C., and Brilakis, I. (2015). "Detection of Multiple Road Defects for Pavement Condition Assessment." Eindhoven, The Netherlands.
Samadzadegan, F., Sarafraz, A., and Tabibi, M. (2006). "Automatic lane detection in image sequences for vision-based navigation purposes." ISPRS Image Engineering and Vision Metrology.
SDDOT. (2009). "SDDOT'S Enhanced Pavement Management System - Visual Distress Survey Manual." South Dakota Department of Transportation.
Tapia-Espinoza, R., and Torres-Torriti, M. (2013). "Robust Lane Sensing and Departure Warning under Shadows and Occlusions." Sensors, 13(3), 3270-3298.
UKPMS. (2005). "The UKPMS user manual." United Kingdom Pavement Management System.
Urmson, C., Anhalt, J., Bagnell, D., Baker, C., Bittner, R., Clark, M. N., Dolan, J., Duggins, D., Galatali, T., Geyer, C., and others. (2009). "Autonomous driving in urban environments: Boss and the urban challenge." The DARPA Urban Challenge, Springer, 1-59.
Werro, P. (2013). "SCANNER surveys."
Wing, M. G., Eklund, A., and Kellogg, L. D. (2005). "Consumer-grade global positioning system (GPS) accuracy and reliability." Journal of forestry, 103(4), 169-173.
Zhang, G., Zheng, N., Cui, C., Yan, Y., and Yuan, Z. (2009). "An efficient road detection method in noisy urban environment." Intelligent Vehicles Symposium, 2009 IEEE, IEEE, 556-561.

